Journal of Electrical Systems and Information Technology 3 (2016) 151–160
www.elsevier.com/locate/jesit

Solution of wind integrated thermal generation system for environmental optimal power flow using hybrid algorithm

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Received 5 February 2015; accepted 16 January 2016
Available online 2 August 2016

Abstract

A new evolutionary hybrid algorithm (HA) has been proposed in this work for environmental optimal power flow (EOPF) problem. The EOPF problem has been formulated in a nonlinear constrained multi objective optimization framework. Considering the intermittency of available wind power a cost model of the wind and thermal generation system is developed. Suitably formed objective function considering the operational cost, cost of emission, real power loss and cost of installation of FACTS devices for maintaining a stable voltage in the system has been optimized with HA and compared with particle swarm optimization algorithm (PSOA) to prove its effectiveness. All the simulations are carried out in MATLAB/SIMULINK environment taking IEEE30 bus as the test system.

Keywords: Hybrid algorithm; Wind integration; Optimal power flow; Optimization

1. Introduction

With gradual degradation in the environmental conditions, power utilities have shifted their focus toward power generation technologies which are non-polluting in nature. In this regard, a grid integrated wind power generation provides an economic and reliable alternative. However, the nature of intermittency of wind flow poses some complex and challenging issues related to the generation scheduling and other operational problems. Owing to the uncertainty of wind flow, accurate estimation of the generated wind power may not be possible. Therefore, a suitable cost component approximating the cost of the under estimation (*UE*) and over estimation (*OE*) of wind power (Jabr and Pal, 2009) compared to the actual availability of the same is considered in the cost of generation (Jabr and Pal, 2009). Authors in Hetzer et al. (2008) have discussed about the additional components of cost which may be used in wind integrated system. Apart from the generation cost, the WECS based on DFIG, poses another problem of managing the system

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http://dx.doi.org/10.1016/j.jesit.2016.01.004

reactive power demands. Because, the power electronics switches used in the converters of DFIG have limited current capacities and therefore also have limited reactive power capabilities (Panda and Tripathy, 2014). With ever increasing WECS based on the DFIG units (Ackermann, 2005), the OPF demands the above issue to be included in its formulation, so that the system remains voltage secure, particularly during *UE* situations. Therefore, to provide additional reactive power support as a means to prevent the degradation of system voltage during *UE* scenario, weak bus in the network is installed with shunt FACTS devices. In this regards role of shunt FACTS devices like the static VAR compensators (SVC) and the STATCOM have been investigated in Molinas et al. (2008) and Yome and Mithulananthan (2005) for their capabilities in supplying reactive power to the system. Owing to the operational flexibility and better dynamic performance in the system, the STATCOM has been found to be more beneficial compared to the SVC. In Niknam et al. (2011), the authors have demonstrated the application of meta-heuristic algorithm to OPF problem of power system equipped with thermal generating units. Modeling of wind variability and incorporation of wind power into power system issues are presented in Seguro and Lambert (2000) and Shi et al. (2012) respectively.

1.1. EOPF formulation

To account for the intermittency of wind flow and to mitigate the cost of operation during any condition of imbalance between available and utilized wind power, a component of cost could be added to the system generation cost. Moreover, the converters of DFIG have restrictions (Engelhardt et al., 2011) of handling reactive power. Therefore, provision of additional reactive power support at the DFIG and other suitable buses should be there to maintain satisfactory system voltage profile. However, due to the superior functionality of STATCOM as discussed above, it has been installed at the weakest node (Acharjee et al., 2011) in the system. This cost of installation of STATCOM is suitably formulated in the problem of OPF. As thermal generation plant burns carbon intensive fuel, they generate more carbon dioxide at increased levels of operation and cause a threat to environmental security. So considering this aspect, in this work wind powered units are used as a means of meeting emissions reduction targets by reducing the stress on thermal generating units. The problem is formulated as follows,

Minimize

$$F = F_1 + F_2 + F_3 \tag{1}$$

In the above equation F_1 corresponds to cost of wind-thermal power generation, F_2 corresponds to cost of real power loss, and F_3 denotes the cost associated with carbon emission from thermal power generators in Rs/ton.

The mathematical interpretation of the above components are described as

$$F_1 = \sum_{t}^{N_g} C_t\left(P_{gt}\right) + \sum_{r}^{N_w} [C_{wr}\left(P_{wr}\right) + C_{p,wr}\left(P_{wr,\text{av}} - P_{wr}\right) + C_{r,wr}\left(P_{wr} - P_{wr,\text{av}}\right)] + C_{\text{VS}} \tag{2}$$

In this expression, notations *t* and *g* denote the thermal units and *r* and *w* denote the wind units. The first term in F_1 is the cost of thermal power generation, second term is the cost of purchase of wind power from the wind power producer, third term is the cost due to under estimation of available wind power and fourth term is the cost due to over estimation of available wind power. Fifth term represents the installation cost of STATCOM which is used as a means to improve the voltage stability by providing necessary reactive power support to the network. These terms are explained as

$$C_t\left(P_{gt}\right) = a_t P_{gt}^2 + b_t P_{gt} + c_t \tag{3}$$

where a_t, b_t, c_t are the cost coefficients of *t*th thermal unit and P_{gt} is the power output of *t*th generator. The details of cost coefficients are given in Table 1.

$$C_{wr}\left(P_{wr}\right) = d_r P_{wr} \tag{4}$$

Table 1
Cost coefficients of thermal generating units.

Generator no.	Cost coefficients			Min limit (MW)	Max limit (MW)
	a_t	b_t	c_t		
1	0.00975	2.5	0	50	200
2	0.0175	1.75	0	20	80
3	0.0625	1.0	0	10	40

Here d_r is the direct cost coefficient of the rth wind generator and P_{wr} is the scheduled power output of rth wind unit. The cost due to under estimation of available wind power may be expressed as

$$\begin{aligned} C_{p,wr}\left(P_{wr,\mathrm{av}} - P_{wr}\right) &= K_{Pr}\left(P_{w\,\mathrm{av}} - P_{wr}\right) \\ &= K_{pr}\int_{P_{wr}}^{P_{ro}} \left(w - P_{wr}\right) f_w(w)\,\mathrm{d}w \end{aligned} \tag{5}$$

In (5), K_{Pr} is the penalty cost coefficient for the rth wind generator and $f_w(w)$ represents the WECS wind power probability density function (PDF) (Seguro and Lambert, 2000), known as Weibull distribution function. P_{wr}, P_{ro}, $P_{w\,\mathrm{av}}$ are respectively the scheduled, rated power and available wind power from rth wind power generator. Cost of over estimation may be expressed as

$$\begin{aligned} C_{\mathrm{R}\,wr}\left(P_{wr} - P_{wr\,\mathrm{av}}\right) &= K_{\mathrm{R}r}\left(P_{wr} - P_{w\,\mathrm{av}}\right) \\ &= K_{\mathrm{R}r}\int_{0}^{P_{wr}} \left(P_{wr} - w\right) f_w(w)\,\mathrm{d}w \end{aligned} \tag{6}$$

The last term of F_1 denotes the cost of installation of shunt FACTS devices in the system to improve the system voltage profile particularly during under-estimation scenario. In (7) K_{SC} is the cost coefficient and Q_{SC} is the reactive power support obtained from STATCOM.

$$C_{\mathrm{VS}} = K_{\mathrm{SC}} \times \left(Q_{\mathrm{SC}}\right) \tag{7}$$

The second term of F, i.e., F_2 represents the cost associated with minimization of real power transmission loss in the system. It may be expressed as

$$F_2 = C_{\mathrm{L}}\left(P_{\mathrm{loss}}\right) \tag{8}$$

Similarly to incorporate and minimize the adverse effect of emission on environment, a cost corresponding to emission of CO_x and SO_x, is added with the objective function. The third term i.e., F_3 which signifies the emission issues may be expressed as

$$\begin{aligned} F_3 &= \sum_{t}^{N_g} C_{\mathrm{E}}\left(P_{gt}\right) \\ &= \sum_{t}^{N_g} 10^{-2}\left(\alpha_t P_{gt}^2 + \beta_t P_{gt} + \gamma_t\right) + \zeta_t \exp\left(\lambda_t P_{gt}\right) \end{aligned} \tag{9}$$

In the above expression

$C_{\mathrm{E}}\left(P_{gt}\right)$ is the cost function for the emission of mentioned atmospheric pollutants.

α_t, β_t, γ_t, ζ_t, λ_t are the coefficients of tth generator emission characteristics.

The above mentioned objective function represented by (1) is subjected to the following constraints.

$$\sum_{t}^{N_g} P_{gt} + \sum_{r}^{N_w} P_{wr} = P_{\mathrm{loss}} + P_{\mathrm{load}} \tag{10}$$

$$\sum_{t}^{N_g} Q_{gt} + \sum_{r}^{N_w} Q_{wr} = Q_{\text{loss}} + Q_{\text{load}} \tag{11}$$

$$\mathrm{P}_{gt}^{\min} \leq \mathrm{P}_{gt} \leq \mathrm{P}_{gt}^{\max} \tag{12}$$

$$Q_{gt}^{\min} \leq Q_{gt} \leq Q_{gt}^{\max} \tag{13}$$

$$V_t^{\min} \leq V_t \leq V_t^{\max} \tag{14}$$

$$P_{wr} \leq P_{wr}^{\max} \tag{15}$$

$$Q_{wr}^{\min} \leq Q_{wr} \leq Q_{wr}^{\max} \tag{16}$$

In the above equations P_{gt}, Q_{gt} are the real and reactive power output of thermal generators where as P_{wr}, Q_{wr} are the corresponding powers of wind powered units.

1.2. Modeling of wind intermittency

Due to some practical limitations in the applicability of statistical methods and nature of unpredictability of wind speed, some works (Seguro and Lambert, 2000; Tsikalakis et al., 2006) have tried to find out the probability distribution functions (PDF), which approximates the variability of wind flow. Similar to the earlier work (Panda and Tripathy, 2014), this study also applies Weibull PDF as explained in (17).

$$f_v(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{(k-1)} e^{-(v/c)^k},\ 0 < v < \infty \tag{17}$$

In (17), c and k are the scale and shape parameters respectively, which together control the extent of variability and pattern of wind flow and v is the wind speed in m/s.

2. Application of intelligent algorithm

2.1. Particle swarm optimization algorithm (PSOA)

In PSO, a set of randomly generated solutions (initial swarm) propagates in the design space toward the optimal solution over a number of iterations (moves) based on large amount of information about the design space that is absorbed and shared by all members of the swarm. PSO is inspired by the activities like flocks of birds, schools of fish to get used to their environment, find affluent resources of food. The basic PSO algorithm considers three steps, namely, generating particles' positions and velocities, velocity update, and finally, position update. The details of the approach may be referred from Valle and Venayagamoorthy (2008).

2.2. Hybrid algorithm

The hybrid algorithm (HA) is synthesized by implementing the mutation strategies of GA along with a modified strategy of BFA that was first proposed in Tripathy and Mishra (2007) and then applied in Panda and Tripathy (2014), so that the optimization efficiencies of both the algorithms may be further improved in some specific problems. The original version of BFA may be referred from Passino (2002). The modified improved version of BFA is similar to the original algorithm, except some modifications, which are elaborated in Tripathy and Mishra (2007). The steps involved in HA can be explained as follows

At the outset, variables like number of control parameters (p), bacteria (S), chemotactic process (N_c), reproduction events (G) and elimination & dispersal events (D) for the algorithm, are initialized. Further, the control parameters like maximum swimming length N_s ($\leq N_c$), the probability of elimination and dispersal P_{ed}, the swarming coefficients i.e.,d_{attract}, ω_{attract}, h_{repelent} and ω_{repelent}, run length unit ($C(i)$) and swim length SL are all chosen judiciously. $P(p,S,1)$, specifies the location of the initial set of S bacteria, each consisting of p random numbers. After scaling up, each of the random numbers represents a possible solution of the control variables.

The iterative steps of HA proceeds as follows. The cost function for the initial bacterial population inside the inner most chemotaxis loop, is evaluated. Any ith bacterium and its corresponding cost function in the jth chemotactic, kth reproduction and lth elimination stages is identified by, $\theta^i(j,k,l)$ and $F(i,j,k,l)$ respectively. j, k, and l are initialized before the first iteration.

1) Begin elimination dispersal loop.
2) Begin reproduction loop.
3) Begin chemotaxis loop.
   a) For $\forall\, i = 1, 2 \ldots S$, calculate the cost function $F(i, j, k, l)$.
   b) Find the optimum bacterium θ_{ob}, from all those evaluated until that point of evolution. $\forall\, i = 1, 2 \ldots S$, determine the swarm attractant cost F_{CC}, that is added with $F(i, j, k, l)$ to obtain $F_{\text{sw}}(i, j, k, l)$ (Passino, 2002).
   c) If $j = 1$
      i) Randomly select two parents of bacteria for reproduction, out of the pool of all S bacteria.
      ii) Generate two random numbers τ_1 and τ_2.
         a) If $\tau_1 \le P_{mutation}$, do *mutation* at the decimal crossover point decided by τ_2.
         b) Else if, $P_{mutation} < \tau_1 \le P_{Crossover}$, do *Crossover* at the decimal crossover point decided by τ_2. It is to be noted that, after the above *GA* operators, $\theta^i(j, k, l)$ has generated *bacterial off springs* $\theta^i_{Cross}(j, k, l)$.
      iii) Carry out *swimming* or *tumbling*, using the following equation

$$\theta^i(j+1, k, l) = \theta^i_{Cross}(j, k, l) + C(i)\frac{\Delta_S(i)}{\sqrt{\Delta_S^T(i)\Delta_S(i)}} \tag{18}$$

where $\Delta_S(i) \in \Re^p$ is a predefined random direction vector, with each element $\Delta_{S_m}(i)$, $m = 1,2,\ldots p$.

d) For, $j > 1$
   i) Repeat steps 3.c. (i) & (ii) and reorienting the $\theta^i_{Cross}(j, k, l)$ through swimming/tumbling.
   ii) If, $F_{\text{sw}}(i, j, k, l) < F_{\text{sw}}(i, j-1, k, l)$ & SL $< N_s$, swim: each bacterium swims for a maximum of N_s times. Evaluate $\theta^i(j+1, k, l)$ using (18). Increment SL i.e., SL = SL + 1.
   iii) Else, tumble: a new direction Δ_N similar to Δ_S, but not predefined as the later. Set $\Delta_S = \Delta_N$,and use Eq. (18) to determine $\theta^i(j+1, k, l)$.
   iv) Reset swim length SL i.e., SL = *0*. The next *bacterial off spring* $(i+1)$ is taken for swimming/tumbling till $i = S$

4) Increment 'j' i.e., $j = j + 1$. Go to step 3, if $j < N_c$ (continue chemotaxis loop).
5) Carry out the process of reproduction
   a) For the given k and l, let $J_{health} = \underset{j\in\{1\cdots N_c\}}{Sort}\{J_{\text{sw}}(j, k, l)\}$. Sort bacteria in order of ascending cost J_{health}. A higher cost of any bacterium means lower health for minimization.
   b) From the total S bacteria, the better half sustains the evolution process replacing the other less healthier half of bacteria, who are eliminated following *elitism*.
   c) Increment the reproduction loop counter i.e., $k = k + 1$. Go to step 2 if $k < G$.
6) In the process of elimination & dispersal, generate a random number τ_3.
   a) If $\tau_3 \le P_{\text{ed}}$, then the existing entire set of bacteria gets eliminated and dispersed in a new random direction. Increment $l = l + 1$. Go to step 1, if $l < D$.
   b) Else continue with reproduction again, i.e., go to step 2.

It can be noticed that in the steps 3.c. (i) & (ii) and 3.d. (i) & (ii), the hybridization of GA operators in the modified BFA (Panda and Tripathy, 2014), is applied. In addition to above, the use of optimum bacterium (θ_{ob}) in evaluation of swarm attractant cost (F_{CC}) in step 3.b, as suggested earlier in Passino (2002), improves its ability to swarm.

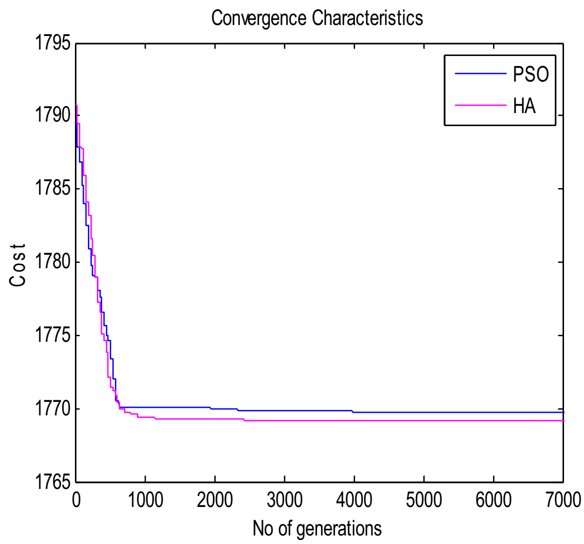

Fig. 1. Convergence characteristics of HA and PSO.

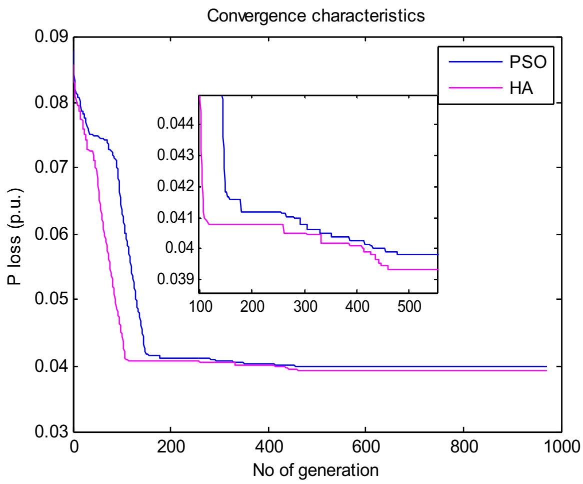

Fig. 2. Convergence characteristics of HA and PSO for real power loss.

3. Simulation result and discussions

For simulation of the work, the IEEE-30 bus test system (Pai, 1996) is considered. The system is modified by replacing conventional generators with wind farms located at fifth, eleventh and thirteenth bus. Each wind farm (WF) consists of several wind turbine coupled with doubly fed induction generators (DFIGs). The STATCOM has been installed (Enrique et al., 2004) at the weakest bus (Acharjee et al., 2011) i.e., at 30th bus.

3.1. *Effectiveness of HA to the proposed system (scenario-1)*

In this scenario-1, the objective function as mentioned by (1) is optimized with both PSOA and HA.

The convergence characteristics obtained by HA and PSOA for the objective function (1) is illustrated in Fig. 1 and optimization of real power transmission loss by the above techniques is shown in Fig. 2. From the figures it can be seen that solutions obtained with the HA converges at 1769.2 where as that with PSO converges at 1769.7. It clearly shows the effectiveness of HA over PSO, in terms of optimization. As evident from Fig. 2, the HA proves its merit in terms of minimizing the real power transmission loss compared to PSO though the difference is not significant.

Table 2
Optimized generation schedule of the generators in *p.u.* with HA and PSOA for scenario 1.

	HA		PSOA	
	P_g	Q	P_g	Q
1	0.6463	0.76532	0.7514	0.6513
2	0.6187	−0.2732	0.6075	−0.2732
5	0.5000	0.0086	0.4514	0.1191
8	0.3251	−0.3698	0.3065	−0.3700
11	0.3791	0.2394	0.3830	0.2986
13	0.3575	0.2521	0.3087	0.2978
Q_{SC}	−0.1105		−0.0835	
P_L	0.0393		0.0398	
TC	1769.2		1769.6	

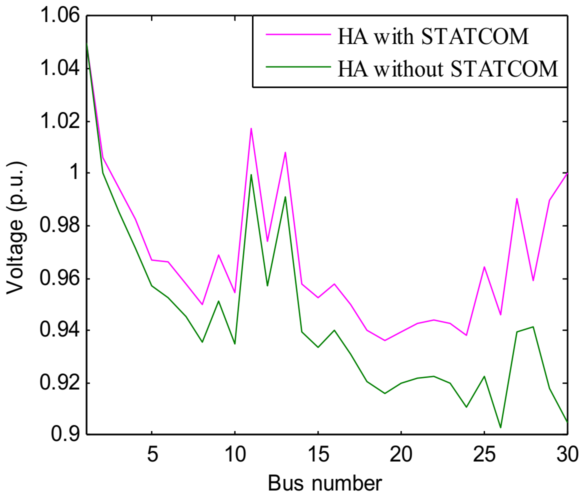

Fig. 3. Improvement of voltage profile after the incorporation of STATCOM.

The details of numerical analysis of the above figures are depicted in Table 2. In order to validate the incorporation of STATCOM in the system in terms of improvement of voltage profile, a comparison is made between two situations. In the first situation, the STATCOM is incorporated and in the second situation STATCOM is not installed in the system. Considerable improvement in the bus voltages profile of the system bus is observed, when the STATCOM is connected in the system. The bus voltage profiles are shown in Fig. 3. The modeling aspects of STATCOM may be referred from Enrique et al. (2004). As depicted in Table 2, the optimum transmission loss obtained with HA is found to be 0.0393 p.u. while with PSOA the value is 0.0398 p.u.

3.2. Cost benefit analysis of emission reduction (scenario-2)

In a wind–thermal scheduling, it is a general practice to include a penalty cost when the scheduled wind power is less than the available wind power (Hetzer et al., 2008). Also in this scenario, more thermal power needs to be scheduled for meeting the load demand (Doherty and O'Malley, 2005). However, a more practical and less expensive approach may be to schedule the wind power as per the available aerodynamic power, thereby saving the penalty cost and decreasing the emission cost, as the thermal units would now generate less. The problem can be modeled according to the above principle during an under estimation scenario, which will lead to maximum utilization of available wind power. Moreover, due to reduction in emission the approach shall be more economic. To demonstrate

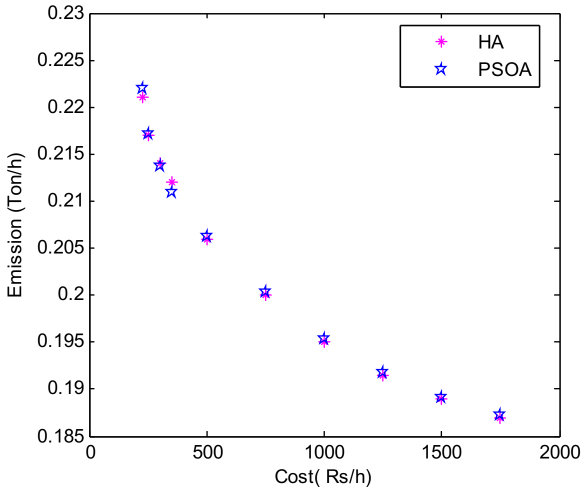

Fig. 4. Pareto optimal representation of cost-emission in 10 separate runs.

Table 3
Best compromised solution of HA and PSOA for the proposed modeling.

Techniques	Best compromised solution for	
	Cost	Emission
HA	1250.6	0.1915
PSOA	1265	0.1935

this in a comparative way, the problem is also treated as a single objective optimization problem by linear combination of cost and emission objectives as follows:

$$\text{Minimize } \omega C_t\left(P_{gt}\right) + (1-\omega)\,\mu \times F_3 \tag{20}$$

where the scaling factor μ is selected as 2000 in this study and ω is a weighting factor. To generate 10 non dominated solutions, the HA and PSOA techniques are applied 10 times with ω varying as a random number between 0–1. The Pareto-optimal front of the above is shown in Fig. 4. Out of the 10 non dominated solutions in the Pareto optimal set, the most non dominated solution obtained both for HA as well as PSOA, are presented in Table 3. As shown, they represent the most suitable costs of generation and emission obtained with the optimization algorithms. While simulating this objective, the cost of meeting the wind intermittency and cost of installation of STATCOM has not been taken into consideration.

From Table 3 it may be concluded that the best compromised solution with HA is resulting with 1250.6 Rs/h which is far less than 1265 Rs/h obtained with PSOA with corresponding reduction of 0.002 ton/h. Therefore, a notion may be drawn that the the proposed HA approach is superior and preserves the diversity of the non dominated solutions over the PSOA front. Thus from the convergence characteristics and the results presented in Tables 2 and 3 the improved performance of HA over PSOA is distinctly demonstrated.

3.3. Environmental benefit of increased wind power production

In order to reduce the stress on conventional generating units, the ISO should emphasize on maximum utilization of available wind resources. Therefore, during *UE* scenario when the actual available wind power is more than that of scheduled value, this additionally available wind power i.e., the surplus amount, when utilized completely can proportionally reduce the burden on conventional generating units. It results in curtailment of equivalent amount

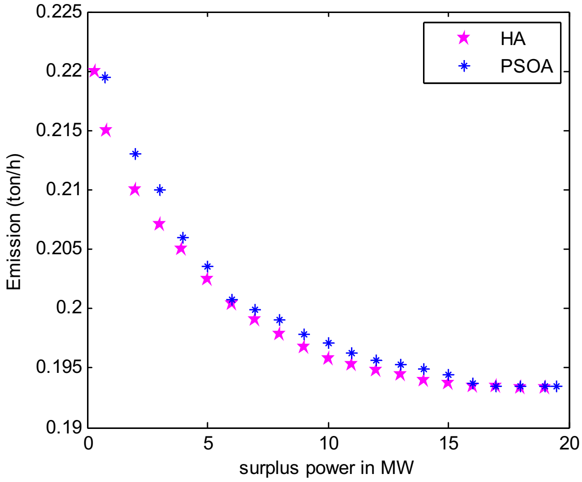

Fig. 5. Pareto optimal representation of power-emission in 20 separate runs.

corresponding to the surplus value (MW) from the non wind powered units, thereby ensuring reduction in emission from their output. To demonstrate this concept the surplus wind power ($P_{sp,r}$) has been calculated using (5) as below.

$$\begin{aligned} P_{sp,r} &= \int_{P_{wr}}^{P_{ro}} \max\left(w - P_{wr}, 0\right) f_w\left(w\right) \mathrm{d}w \\ &= \int_{P_{wr}}^{P_{ro}} \left(w - P_{wr}\right) f_w\left(w\right) \mathrm{d}w \end{aligned} \tag{21}$$

The relation between $P_{sp,r}$ and corresponding reduction in emission, formulated as a single objective function optimized with HA and PSOA separately, is demonstrated in Fig. 5. Here HA proves its superiority over PSOA in getting the Pareto solution.

4. Conclusion

In this paper, an approach based on combination of genetic algorithm and bacteria foraging algorithm i.e., HA has been developed and applied to environmental optimal power flow problem in a multi-objective optimization framework with competing fuel cost and environmental impact objectives. Its effectiveness is compared with PSOA for different operational objectives. The HA is found to be better than PSOA in terms of obtaining better convergence characteristics for both wind-thermal operational cost, transmission loss and environmental cost. The results show that the proposed HA approach is efficient for solving multi objective optimization where multiple Pareto-optimal solutions can be found in single simulation run. Additionally, the non dominated solutions in the obtained Pareto-optimal solution with HA are well dispersed and have acceptable assortment characteristics.

References

Acharjee, P., Mallick, S., Thakur, S.S., Ghoshal, S.P., 2011. Detection of maximum loadability limits and weak buses using Chaotic PSO considering security constraints. Chaos Solitons Fractals 44, 600–612.

Ackermann, T., 2005. Wind Power in Power System. John Wiley & Sons.

Doherty, R., O'Malley, M., 2005. New approach to quantify reserve demand in systems with significant installed wind capacity. IEEE Trans. Power Syst. 20 (May (2)), 587–595.

Engelhardt, S., Erlich, I., Feltes, C., et al., 2011. Reactive power capability of wind turbines based on doubly fed induction generators. IEEE Trans. Energy Convers. 26 (1), 364–372.

Enrique, A., Claudio, R., Fuerte-Esquivel, Ambriz Perez, 2004. FACTS Modeling and Simulation in Power Network. John Wiley & Sons Ltd.

Hetzer, J., Yu, D.C., Bhattarai, K., 2008. An economic dispatch model incorporating wind power. IEEE Trans. Energy Convers. 23 (2), 603–611.

Jabr, R.A., Pal, B.C., 2009. Intermittent wind generation in optimal power flow dispatching. IET Gener. Transm. Distrib. 3 (1), 66–74.
Molinas, M., Suul, J.A., Undeland, T., 2008. Low voltage ride through of wind farms with cage generators: STATCOM versus SVC. IEEE Trans. Power Electron. 23 (3), 1104–1117.
Niknam, T., Narimani, M.R., Jabbari, M., et al., 2011. A modified shuffle frog leaping algorithm for multi objective optimal power flow. Energy 53, 6420–6432, Elsevier.
Pai, M.A., 1996. Computer Methods in Power System Analysis. TMH Publishers.
Panda, A., Tripathy, M., 2014. Optimal power flow solution of wind integrated power system using modified bacteria foraging algorithm. Int. J. Electr. Power Energy Syst. 54, 306–314, Elsevier.
Passino, K.M., 2002. Biomimicry of bacterial foraging for distributed optimization and control. IEEE Control Syst. Mag. 22 (3), 52–67.
Seguro, J.V., Lambert, T.W., 2000. Modern estimation of the parameters of the Weibull wind speed distribution for wind energy analysis. J. Wind Eng. Ind. Aerodyn. 85, 15–84.
Shi, L., Wang, C., Yao, L., et al., 2012. Optimal power flow solution incorporating wind power. IEEE Syst. J. 6 (2), 233–241.
Tripathy, M., Mishra, S., 2007. Bacteria foraging based solution to optimize both real power loss and voltage stability limit. IEEE Trans. Power Syst. 22 (1), 240–248.
Tsikalakis, A.G., Katsigiannis, Y.A., Georgilakis, P.S., Hatziargyriou, N.D., 2006. Determining and exploiting the distribution function of wind power forecasting error for the economic operation of autonomous power system. IEEE Power Engineering Society General Meeting.
Valle, Y., Venayagamoorthy, G.K., 2008. Particle swarm optimization: basic concepts, variants and applications in power systems. IEEE Trans. Power Syst. 12 (2), 171–195.
Yome, A.S., Mithulananthan, N., 2005. Static voltage stability margin enhancement using STATCOM, TCSC and SSSC. In: IEEE/PES Transmission and Distribution Conference, China, pp. 1–6.

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